Assessing Technology Readiness for Artificial Intelligence and Machine Learning based Innovations

Tobias Eljasik-Swoboda[1][a], Christian Rathgeber[1] and Rainer Hasenauer[2]
[1]ONTEC AG, Ernst-Melchior-Gasse 24/DG, Vienna, Austria
[2]Marketing Management Institute, Wirtschaftsuniversität Wien and Hi-Tech Center, Vienna, Austria

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Abstract: Every innovation begins with an idea. To make this idea a valuable novelty worth investing in requires identification, assessment and management of innovation projects under two primary aspects: The Market Readiness Level (MRL) measures if there is actually a market willing to buy the envisioned product. The Technology Readiness Level (TRL) measures the capability to produce the product. The READINESSnavigator is a state of the art software tool that supports innovators and investors in managing these aspects of innovation projects. The existing technology readiness levels neatly model the production of physical goods but fall short in assessing data based products such as those based on Artificial Intelligence (AI) and Machine Learning (ML). In this paper we describe our extension of the READINESSnavigator with AI and ML relevant readiness levels and evaluate its usefulness in the context of 25 different AI projects.

1 INTRODUCTION

Innovation is an important foundation for entrepreneurial success and has great economic importance (Niever et al., 2019). But what do the terms innovation, success and even invention actually mean? According to Rogers (2003), *"invention is the process by which a new idea is discovered or created; the adoption of an innovation is the process of using an existing idea"*. Another definition for invention and innovation is that an invention is not necessarily positive and can be purely imagined while an innovation aims to create value (Merriam-Webster, 2019). According to Schumpeter (1939), an idea and technical solution leads to an invention, which can become an innovation by a successful market launch. In short, an invention can be regarded as an idea while an innovation strives to be a successful and profitable invention.

There are multiple measures to define success and profitability for innovations. The classic approach is to measure success as maximum monetary return on investment. Another more modern approach is to consider the *triple bottom line*, which is defined as the tradeoffs between economic drivers (the monetary return on investment), environmental impact and social impact of the innovation (Hasenauer et al., 2016). Examples for data based Machine Learning (ML)- and Aritificial Intelligence (AI) innovation projects aiming for a triple bottom line include Social Assistive Robots for Elderly Care (SAR) and Sensor Enabled Affective Computing for Enhancing Medical Care (SENSECARE) (Belviso et al., 2018), (Donovan et al., 2018), (Healy et al., 2018). SAR aims to develop caregiving robots for the elderly, SENSECARE aims to monitor dementia patients using AI so that they can continue living in their home and help can be alerted if necessary. Wellbeing of elderly or dementia patients are important aspects in these innovation projects, not solely the monetary return on investment. Lepak et al. (2007) aim to define *value creation* and have shown, that the concept is heterogeneously used depending on the academic field of study. Creators and users of value can differ and stretch from society, over organizations to individuals which all have different value creation and capture processes.

[a] https://orcid.org/0000-0003-2464-8461

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However one decides to measure success, in order to achieve it, innovations must be managed and assessed with regards to their readiness (Hasenauer et al., 2015). Investors are highly unlikely to provide capital for innovations that are not ready. To facilitate informed decisions, two dimensions of readiness need to be assessed: The Technology Readiness Level (TRL) expresses the degree of readiness for a technology while the Market Readiness Level (MRL) measures the maturity of a given need in the market considering potential obstacles (Sadin et al., 1989)(Dent and Pettit, 2011).

The READINESSnavigator is a software product that addresses the identification, assessment, management and protection of investments through analyzing innovations for their triple bottom line by assessing their TRL and MRL (Ontec, 2019). Its underlying methodology has been used in the assessment of 57 startups and 26 high-tech products. Hasenauer et al. (2016) have shown that startups that used the READINESSnavigator's underlying readiness assessment method had a significantly higher success rate than startups not following this approach. More details about the method and tool can be found in section 2. Even though the underlying TRL and MRL models are market and technology versatile, they do not express the specific problems associated with innovations in the field of Artificial Intelligence (AI) and Machine Learning (ML). To overcome this shortcoming, our research goals are to identify and specify levels of readiness for AI and ML. We subsequently implement this model as extension for the READINESSnavigator and use it in the assessment of 25 AI innovations to experimentally evaluate its usefulness.

To do so, this paper is structured as follows: Section two describes the relevant state of the art in science and technology for our endeavour. Section three describes our AI readiness model, which we implemented as extension of the READINESSnavigator. Section four describes our observations in using the READINESSnavigator for AI while section five finishes our contribution by describing conclusions drawn from our observations.

2 STATE OF THE ART

The idea to model readiness of technologies was originally conceived by NASA in 1974 and formally defined in 1989 (Sadin et al., 1989). Dent and Pettit (2011) adopted the concept to include market readiness. Hasenauer et al. (2015) built on this to propose a framework to manage technology push which was extended to also address the triple bottom line (Hasenauer et al., 2016). The READINESSnavigator was developed by Ontec in colaboration with Hasenauer et al. to aid in documenting and accessing innovations and their respective readiness levels.

While NASA uses nine levels of technology readiness, from basic idea to flight proven on missions, Hasenauer et al. (2015) define three dimensions of technology readiness which are each expressed in nine levels: *Intellectual property readiness* (IPR-RL) expresses if the underlying intellectual property has been protected, *integration readiness* (INT-RL) expresses if the technology can be integrated where needed by the envisioned customers while *manufacturing readiness* (MAN-RL) expresses if the innovation can actually be produced.

The market readiness is likewise split into four dimensions. The *competitive supply readiness* (COM-RL) expresses if competitors have similar products and how much the innovator is aware of - and has evaluated them. The *demand readiness* (DEM-RL) assesses if there is a demand for the product. The *customer readiness* (CUS-RL) expresses if a customer is ready to use and adopt the product while the *product readiness* (PRO-RL) expresses if the product itself is ready for widespread use. Figure 1 illustrates a visualization module within the READINESSnavigator. In this example, an Innovation has a very high MAN-RL but poor IPR-RL and mediocre MRL levels. The READINESSnavigator highlights fields of action and shows the necessity to address issues in certain fields to raise overall readiness, for example by addressing intellectual property rights issues. Hasenauer et al. (2016) have shown a success optimizing development curve in which market readiness always is one or two levels above technologry readiness during product development. The intuition for this curve is simple: If potential customers are willing to purchase an innovation, further technology development can be financed by this revenue. The READINESSnavigator compares an innovation's current development with the success optimizing curve to highlight necessary next steps.

As part of technology readiness, *manufacturing readiness* strongly focuses on the capability to produce physical goods. As the benefits of AI and ML are much more data and information based, their readiness comes with an additional set of challenges.

There is some work in assessing AI readiness by multiple organisations. Intel (2019) published a model for AI readiness that assesses organisations.

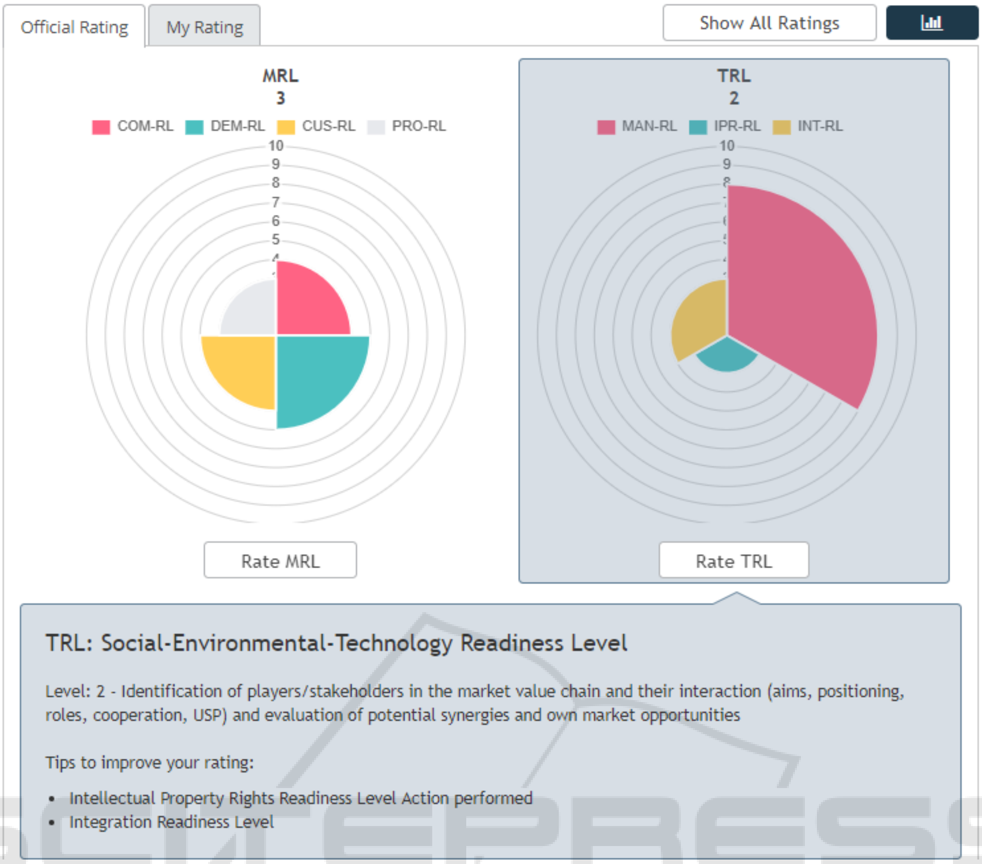

Figure 1: READINESSnavigator visualization.

They address three dimensions of AI readiness: *Foundational AI readiness* expresses if the appropriate infrastructure (hard-, and software) is available. *Operational AI readiness* expresses if the necessary management mechanisms are in place. *Transformational AI readiness* expresses how ready an organisation is to maximize the value it obtains from applying AI. According to Intel (2019), there are three fundamental levels for companies in regard to AI readiness: *New to AI*, *ready to scale up*, and *broadly implementing*.

Capgemini Consulting has created an AI readiness benchmark for countries that measures the countries competitiveness regarding AI in terms of *institutional readiness*, *IT maturity* and *available IT skills* (Tinholt et al., 2018). Neither Intel's nor Capgemini's model focuses on the necessary readiness dimensions to innovate. Obviously one can see a start-up as a company which needs to have AI readiness in Intel's sense of the term in order to have any technology readiness. The ability to create beneficial innovations goes beyond Intel's three dimensions as shown in section three of this paper.

Big Data is a related field to AI and ML, which has many overlaps. In order to better understand Big Data endeavours, Kaufmann (2016) proposed the Big Data Management Meta Model (BDMcube). The BDMcube is based on epistemology and sees Big Data as continuous cycle in which the results of data analysis influence the world (*effectuation*). Physical signals are gathered (*datafication*) to be centrally stored (*data integration*), *analysed* and *interacted* with resulting in a new innovation or decision support for any enterprise. Based on this value cycle, Kaufmann et al. (2017) created and evaluated the Big Data Management Canvas (BDMC). The BDMC takes the five cycle stages of the BDMcube and assigns each of them a technical and a business dimension. Each of these 10 dimensions represents a field of action for any big data endeavour. On top of these 10 fields, there are two meta-fields of data intelligence which Kaufmann et al. define as the ability to execute in terms of available skills and infrastructure. Both data intelligence fields clearly have connections to Intel's and Capgemini's views on AI readiness: Without the necessary skills or equipment one cannot carry out any Big Data or AI endeavour. The epistemological value cycle is especially interesting because of *nescience*. In information science, *nescience* is the unawareness of an information need. One could refer to it as *unknown unknown*. Ignorance on the other hand is knowingly not having information, which in contrast can be referred to as a *known unkown* (Weber et al., 2018). The cycle of creating knowledge that leads to a new information need is neatly modelled by the BDMC.

3 MODEL

The READINESSnavigator's technology readiness currently assesses three fields of technology readiness. *Intellectual property readiness* and *integration readiness* are equally as important for AI or ML based innovations as for any other. The *manufacturing readiness* however is not directly applicable, as the challenges of physical production are often times out of scope for ML or AI endeavours. Instead of manufacturing readiness, we propose six AI specific readiness dimensions, split into two main categories of *AI readiness* and *data readiness*. We base these dimensions on the existing state of the art by (Sadin et al., 1989), Hasenauer et al. (2016), Kaufmann et al. (2017), Tinholt et al., (2018) and Intel (2019) as well as five years of practical experience in implementing ML and AI based systems.

It is noteworthy that readiness dimensions are optional within the READINESSnavigator. This means that if one field of readiness is superfluous for a specific innovation, one can always skip assessing it. The overall readiness level of an innovation is its lowest readiness level in one dimension (see Figure 1). Levels within one dimension are always strictly ordered. This means that an innovation cannot reach a higher level if it has not fulfilled all requirements of the previous levels. Currently, all readiness fields have exactly nine levels.

Figure 2 maps AI- and data readiness levels onto the BDMC's fields of action. It also illustrates important links between readiness levels. Different from the existing technology readiness model, the individual levels of different fields can have prerequisites. One can for example not run the envisioned algorithm on relevant real-world data if one doesn't have access to this data.

The first important readiness level for AI is *specification readiness*. For now, it has six different levels that express how clearly the use case for AI is defined. These range from having a vague idea of applying AI to a complete specification. An important intermediate level is level five, which defines success criteria for the AI innovation. These are important for many other fields, for example when defining effectiveness measures for machine learning based applications. Figure 2 illustrates this with the arrow from *specification readiness* to *algorithmic readiness*. Having only six *specification readiness* levels spotlights, that the computation of an innovation's overall readiness level needs to normalize r eadiness levels in order to generate

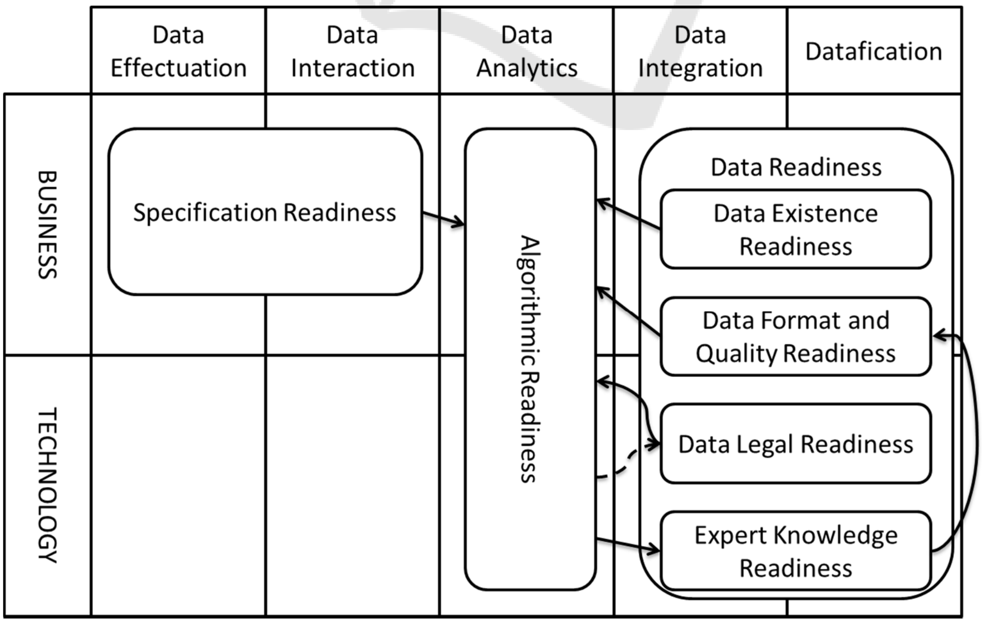

Figure 2: Mapping of our proposed readiness levels on Kaufmann et al.'s BDMC.

meaningful progress graphs similar to those shown in figure 1. We have abstained from inventing redundant readiness levels just to get up to nine levels.

Specification readiness is related to the BDMC's fields of *effectuation* and *interaction* by assessing if there is a specification of what the invention should achieve how users interact with it and how its success can be measured. Also similar to the BDMC method, the specification influences the *analytics* field. We refer to readiness in the BDMC fields of analytics as *algorithmic readiness*. It has eight levels which model stages from knowing no algorithmic approach to solve the issue at hand to using algorithms for this specific problem in production. In between the algorithm family has to be identified. Possible algorithm families include classification, regression, clustering, time-series analysis, structural equation models, fuzzy logic applications or symbolic knowledge reasoning among many others. This obviously depends on the goals specified within the *specification* readiness. Stage four of *algorithmic readiness* expresses the selection of effectiveness measures. E.g. for the classification task, the difference between precision and recall can have massive impacts on the result. Other important levels of *algorithmic readiness* are level 5, indicating that the algorithm is being evaluated using real world data and level 6, indicating that the hyper-parameters are tuned. Hyper-parameter tuning does not necessarily yield good results when the data readiness is poor, because one potentially overfits a solution to inaccurate data. Additionally, low quality data can lack important features resulting in poor system convergence with extreme computation times. To reach levels > 4 of algorithmic readiness, real world quality data must be available.

This creates a link to the main category of *data readiness*. This field is related to Intel's *operational AI readiness* and Capgemini's *IT maturity* fields in the sense that it measures how accessible and understood the necessary data for the envisioned analytics are. As such, we place it in Kaufmann et al.'s (2017) fields of *data integration* and *datafication*. Because readiness levels are supposed to be mono-dimensional, we split up the main category into four individual readiness dimensions. The relevance of all four fields depends on the *specification readiness* and *algorithm readiness*.

Data existence readiness expresses if the required data for the envisioned algorithm actually exists. While this could be expressed in two levels, we opted for nine different levels taking the possibility to gather non-existing data into account. These nine *data existence* levels closely mirror Sadin et al.'s (1989) original NASA technology readiness levels, substituting the readiness of flight hardware with that of data gathering technology so that level one implies that no data exists and one is unaware of a method to gather it while level nine reflects existing data and a productive data gathering technology and process.

Data format and quality readiness reflects how well the existing data format is understood and of what quality the available data is. Understanding the data format is of high importance to create any feature extraction scheme required for ML based algorithms. Having quality data is equally as important so that the resulting innovation actually fulfils its specified goals. Our model expresses these issues using 5 levels that identify if the format is understood, a method to measure quality is identified and data actually is of high quality. Low data quality can manifest itself in multiple ways, such as pragmatic quality, semantic quality, syntactic quality and social quality (Shanks and Corbitt, 1999). While low pragmatic, semantic and syntactic quality point to irregularities in the data model and entries, low social quality data can reflect a high degree of biases If a machine learns to simulate these biases, it automatically creates biased results. Biased AI systems based on their underlying data are problematic as Caliskan et al. (2017), Sweeney (2013) and Holstein et al. (2019) among many others point out. Such a bias doesn't need to be exclusively social. Tasks such as fraud detection, text classification and detection of oil spills in satellite images oftentimes work with 1 positive example out of 100,000 negative examples (Chawla et al., 2002). If such imbalance is the case, it must be understood and addressed in the AI system, which is modelled by our readiness levels.

Data legal readiness is another important aspect modelling the legality of data usage. The General Data Protection Regulation (GDPR) aims at protecting the personal data of EU citizens (EU 2016). It is exemplary for multiple pieces of legislature that regulate how and by whom data can be used. If one wants to base an innovation on processing data, one needs to be sure that it is legal to do so. We model this circumstance using eight different stages. At level one, the legality of data usage is completely unclear where as at level eight there is a Supreme Court ruling explicitly allowing the use of this kind of data. In our model, one does not need to take a lawsuit through all instances before launching an innovation. One should however be aware of potential risks along the way. Important intermediate steps are the identification if natural person's personal data is used because it is much more protected than other types of data. If this is the case, at least within the EU the extra requirement of being capable to explain the AI's results manifest as the GDPR states that every EU citizen has the right of explanation why a specific result was generated. This is also expressed within our eight *data legal readiness* levels. An important aspect of every product launch is to perform a *Freedom to Operate* (FTO) analysis, which is a patent information process that determines if an innovation does not infringe on any existing patents (European Patent Office, 2016). In the case of critical data being used as resource for an innovation, a similar analysis must occur to reach high *data legal readiness*.

Expert knowledge readiness is our final group of readiness levels. It is of particular importance if a symbolic AI is implemented. In contrast to a machine learning based AI, a symbolic AI explicitly models rules in human-readable form (Haugeland, 1985). If one plans to implement a symbolic AI, one needs to capture the necessary domain knowledge from relevant domain experts. Some degree of explicitly modelled domain knowledge might also be required for ML based AI innovations for example for labelling training data. Neural-symbolic integration is the act of constructing hybrid machine learning / symbolic systems (Bader and Hitzler, 2005). No matter what kind of ML or AI based innovation is implemented, checking for access to the required expert knowledge is important to ascertain the innovation's readiness. An *expert knowledge readiness* level of one indicates that the knowledge domain is not yet identified let alone any necessary knowledge captured in a meaningful way. In contrast at level 7, high quality (see *data format and quality readiness*) expert knowledge is captured in a machine readable fashion. Important intermediate steps are the identification of appropriate experts and signing collaboration contracts with them before capturing their knowledge.

In its current version, the READINESSnavigator models readiness levels as entries within a relational database. We implemented our prototype by importing our proposed readiness levels into that database. As of now, the READINESSnavigator lacks two features our model ultimately requires: The capability to model interdependencies between readiness levels and normalization for readiness categories with less than nine levels.

4 OBSERVATIONS

We used the READINESSnavigator AI extension on 25 ideas to determine their potential for becoming successful innovations. At this point in time, none of

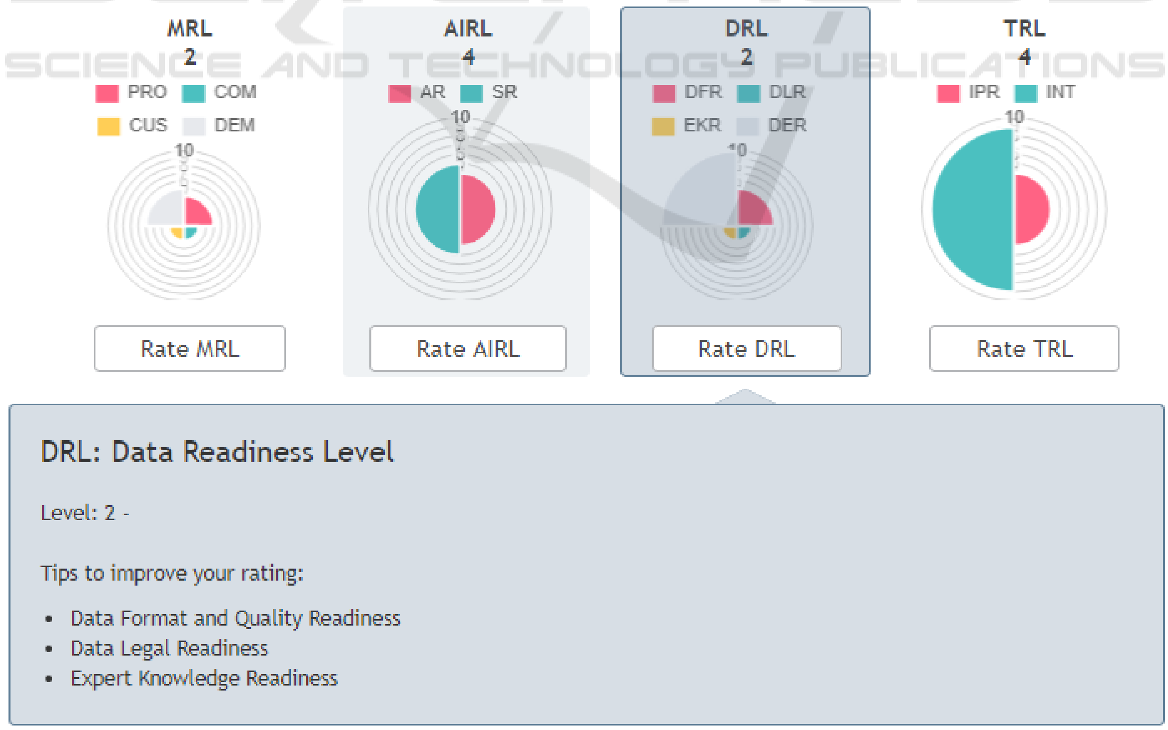

Figure 3: READINESSnavigator showing all proposed readiness levels.

these ideas has been fully implemented and marketed. As we also have no control group capable of measuring the success of AI innovations not using the READINESSnavigator, we cannot yet reliably prove its positive impact on the innovation process.

The following observations were made while working with the READINESSnavigator for AI:

1. The READINESSnavigator prevents that important aspects during the innovation process are overlooked as it demands assessment.

2. The READINESSnavigator helps to steer innovation projects by highlighting weaknesses required for a successful market launch.

3. During this evaluation, the READINESSnavigator for AI was used in a predominately technical company. This means, that the more technology dependent readiness levels were typically higher than those of *market readiness*, *intellectual property rights readiness* and *data legal readiness*. These can require legal counsel and market research, which the company would need to outsource thus creating additional external cost. This effect can be considered as a structural bias as engineering firms usually excel at engineering tasks while legal or marketing firms excel at their specific tasks. The aforementioned bias should be taken into account when planning, staffing and managing innovation projects.

Figure 3 shows a screenshot of the current version of the Readiness Navigator. It shows its current lack of normalizing readiness levels. This especially impacts the data readiness diagrams, where the available levels range from 5 (*data format and quality readiness*) to 9 (*data existence readiness*).

From the 25 ideas used to evaluate the READINESSnavigator for AI, one is closer to market introduction than the remaining 24. When this specific innovation was first assessed, its manually normalized *AI readiness* lacked one level behind its *technology readiness*. The reason for this was, that a concrete learning target has not been defined reducing its *specification readiness*. Similarly, market readiness was one level below the optimal curve, requiring the definition of specific product options in order to raise its *product readiness*. Both issues were remedied before the subsequent implementation began. During technology development, the READINESSnavigator was used as a scenario-modelling tool to see where the readiness levels would be after development if no market readiness related activities were undertaken. In this scenario, after successful development, normalized *technology*-, *data*-, and *AI readiness* are at levels >6. To be on Hasenauer et al.'s (2016) optimal curve, *market readiness* should be >7. This created an additional list of work packages to be addressed in parallel to the technology development.

This specific project highlights our third observation: Technical personnel tends to dismiss the necessity of marketing and sales related activities. The READINESSnavigator for AI helped to raise awareness and lead to the initialization of the required work packages. Additionally, the READINESSnavigator's assessment was used to convince investors, that the development is on track and likely successful.

5 CONCLUSIONS

We started work on the READINESSnavigator AI extension because we are convinced of its positive impact on ML or AI innovation projects. This conviction comes from the basic READINESSnavigator's significant positive impact on other high-technology innovation projects and the solid literature foundation of our proposed ML and AI readiness levels. Using this tool, we evaluated a backlog of 25 potential AI based innovations to determine which have the highest potential for success. At the point of writing this paper, the most promising innovation was nearing market introduction. The READINESSnavigator externalizes expert knowledge about the innovation process to help at every phase of it. This way it functions as automated innovation coach/mentor.

The READINESSnavigator highlights weaknesses in plans. For instance a system can be at a highly algorithmic ready level but lacking legal prerequisites and potential customers if the market readiness is too low.

In future works we intend to either implement or stop work on the innovation projects in our backlog. Stopping work with a too low success probability is equally as much a success for the READINESSnavigator for AI as successful projects. Using a control group of innovation projects not using the READINESSnavigator for AI can prove its usefulness in future works.

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